Business Understanding

The company is looking to expand into the film industry and create its own film studio! I have been tasked to analyze which film genres and types are most successful currently. My challenge was to determine what types of movies and creative talent would be best for our new studio.

Data Understanding

I utilized data sets from IMDB and Box Office Mojo to perform my analysis. The IMDB data was stored as a SQLIte database and contained information on average movie ratings, directors, actors, locations, runtimes, genres, and titles. Box Office Mojo contained the info on which studios produced which movies, how much gross revenue each title generated, and year of release.

Data Preparation

Importing the necessary libraries.

In [1]:
```
import numpy as np
import pandas as pd
from scipy import stats
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```
Movie_Gross = pd.read_csv("bom.movie_gross.csv.gz")
```

In [61]:
```
import sqlite3
conn = sqlite3.connect('im.DB.db')
```

Exploratory Data Analysis

Assessing the tables in the IMDb data.

In [62]:
```
pd.read_sql("""
SELECT * FROM movie_basics;
"""
, conn)
```

Out[62]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy
...	...	...	...	...	...	...
146139	tt9916538	Kuambil Lagi Hatiku	Kuambil Lagi Hatiku	2019	123.0	Drama
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	NaN	Documentary
146141	tt9916706	Dankyavar Danka	Dankyavar Danka	2013	NaN	Comedy
146142	tt9916730	6 Gunn	6 Gunn	2017	116.0	None
146143	tt9916754	Chico Albuquerque - Revelações	Chico Albuquerque - Revelações	2013	NaN	Documentary

146144 rows × 6 columns

In [63]:
```
pd.read_sql("""
SELECT * FROM movie_ratings;
"""
, conn)
```

Out[63]:

	movie_id	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21
...	...	...	...
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

73856 rows × 3 columns

In [65]:
```
pd.read_sql("""
SELECT primary_title AS Title, genres AS Genre, movie_id AS ID, averagerating AS Rating, numvotes AS Votes FROM movie_ba
JOIN movie_ratings
    USING(movie_id)
WHERE Rating >= 7
GROUP BY genres
ORDER BY Rating DESC
;
""", conn)
```

Out[65]:

	Title	Genre	ID	Rating	Votes
0	From Shock to Awe	Documentary,War	tt7541970	9.7	6
1	Love on a Leash	Documentary,Family,Romance	tt1740810	9.7	25
2	Foosballers	Comedy,Documentary,Sport	tt10146728	9.7	22
3	Some Called Them Baby Killers... We Call Them ...	Documentary,Drama,War	tt1791606	9.4	5
4	Lost Conquest	Comedy,Documentary,Fantasy	tt4135932	9.4	5
...	...	...	...	...	...
676	The Secret Reunion	Action,Drama	tt1535491	7.0	3218
677	The Curse of Babylon	Action,Crime,Sci-Fi	tt2118739	7.0	24
678	Carpet Racers	Action,Comedy,Documentary	tt1512738	7.0	44
679	Cheburashka	Action,Animation,Family	tt3676322	7.0	116
680	1 Way Up: The Story of Peckham BMX	Action,Animation,Documentary	tt2959680	7.0	32

681 rows × 5 columns

Inspecting the Movie_Gross CSV file,

In [68]:
```
Movie_Gross
```

Out[68]:

	title	studio	domestic_gross	foreign_gross	year	total_gross	title_clean
0	Toy Story 3	BV	415000000.0	652000000.0	2010	1.067000e+09	toy story 3
1	Alice in Wonderland (2010)	BV	334200000.0	691300000.0	2010	1.025500e+09	alice in wonderland (2010)
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000.0	2010	9.603000e+08	harry potter and the deathly hallows part 1
3	Inception	WB	292600000.0	535700000.0	2010	8.283000e+08	inception
4	Shrek Forever After	P/DW	238700000.0	513900000.0	2010	7.526000e+08	shrek forever after
...	...	...	...	...	...	...	...
3382	The Quake	Magn.	6200.0	NaN	2018	NaN	the quake
3383	Edward II (2018 re-release)	FM	4800.0	NaN	2018	NaN	edward ii (2018 re-release)
3384	El Pacto	Sony	2500.0	NaN	2018	NaN	el pacto
3385	The Swan	Synergetic	2400.0	NaN	2018	NaN	the swan
3386	An Actor Prepares	Grav.	1700.0	NaN	2018	NaN	an actor prepares

3387 rows × 7 columns

Creating a total gross revenue column for easy reference.

In [21]:
```
Movie_Gross['domestic_gross'] = pd.to_numeric(Movie_Gross['domestic_gross'], errors='coerce')
Movie_Gross['foreign_gross'] = pd.to_numeric(Movie_Gross['foreign_gross'], errors='coerce')
Movie_Gross['total_gross'] = Movie_Gross['domestic_gross'] + Movie_Gross['foreign_gross']
Movie_Gross.head()
```

Out[21]:

	title	studio	domestic_gross	foreign_gross	year	total_gross
0	Toy Story 3	BV	415000000.0	652000000.0	2010	1.067000e+09
1	Alice in Wonderland (2010)	BV	334200000.0	691300000.0	2010	1.025500e+09
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000.0	2010	9.603000e+08
3	Inception	WB	292600000.0	535700000.0	2010	8.283000e+08
4	Shrek Forever After	P/DW	238700000.0	513900000.0	2010	7.526000e+08

Now I am going to merge the data from the IMDb dataset with the data from the Box Office Mojo data frame to easily compare information. The Box Office Mojo CSV contains information on gross revenue, which will be necessary for proper analysis.

In [69]:
```
query = """
SELECT * FROM movie_basics
LEFT JOIN movie_ratings ON movie_basics.movie_id = movie_ratings.movie_id
;
"""

imdb_df = pd.read_sql_query(query, conn)
imdb_df.head()
```

Out[69]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	movie_id	averagerating	numvotes
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	tt0063540	7.0	77.0
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	tt0066787	7.2	43.0
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama	tt0069049	6.9	4517.0
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama	tt0069204	6.1	13.0
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	tt0100275	6.5	119.0

In [70]:
```
Movie_Gross['title_clean'] = Movie_Gross['title'].str.lower().str.strip()
Movie_Gross['year'] = Movie_Gross['year'].astype(int)

imdb_df['title_clean'] = imdb_df['primary_title'].str.lower().str.strip()
imdb_df['year'] = imdb_df['start_year'].astype(int)
```

In [71]:
```
merged_df = pd.merge(Movie_Gross, imdb_df, how='inner', on=['title_clean', 'year'])
merged_df.head()
```

Out[71]:

	title	studio	domestic_gross	foreign_gross	year	total_gross	title_clean	movie_id	primary_title	original_title	start_year	runtime_minute
0	Toy Story 3	BV	415000000.0	652000000.0	2010	1.067000e+09	toy story 3	tt0435761	Toy Story 3	Toy Story 3	2010	103
1	Inception	WB	292600000.0	535700000.0	2010	8.283000e+08	inception	tt1375666	Inception	Inception	2010	148
2	Shrek Forever After	P/DW	238700000.0	513900000.0	2010	7.526000e+08	shrek forever after	tt0892791	Shrek Forever After	Shrek Forever After	2010	93
3	The Twilight Saga: Eclipse	Sum.	300500000.0	398000000.0	2010	6.985000e+08	the twilight saga: eclipse	tt1325004	The Twilight Saga: Eclipse	The Twilight Saga: Eclipse	2010	124
4	Iron Man 2	Par.	312400000.0	311500000.0	2010	6.239000e+08	iron man 2	tt1228705	Iron Man 2	Iron Man 2	2010	124

In [72]:
```
merged_df.to_csv('merged_movie_data.csv', index=False)
```

In [73]:
```
merged_df['domestic_gross'] = pd.to_numeric(merged_df['domestic_gross'], errors='coerce')
merged_df['foreign_gross'] = pd.to_numeric(merged_df['foreign_gross'], errors='coerce')
merged_df['worldwide_gross'] = merged_df['domestic_gross'] + merged_df['foreign_gross']
merged_df.head()
```

Out[73]:

	title	studio	domestic_gross	foreign_gross	year	total_gross	title_clean	movie_id	primary_title	original_title	start_year	runtime_minute
0	Toy Story 3	BV	415000000.0	652000000.0	2010	1.067000e+09	toy story 3	tt0435761	Toy Story 3	Toy Story 3	2010	103
1	Inception	WB	292600000.0	535700000.0	2010	8.283000e+08	inception	tt1375666	Inception	Inception	2010	148
2	Shrek Forever After	P/DW	238700000.0	513900000.0	2010	7.526000e+08	shrek forever after	tt0892791	Shrek Forever After	Shrek Forever After	2010	93
3	The Twilight Saga: Eclipse	Sum.	300500000.0	398000000.0	2010	6.985000e+08	the twilight saga: eclipse	tt1325004	The Twilight Saga: Eclipse	The Twilight Saga: Eclipse	2010	124
4	Iron Man 2	Par.	312400000.0	311500000.0	2010	6.239000e+08	iron man 2	tt1228705	Iron Man 2	Iron Man 2	2010	124

In [74]:
```
merged_df.describe()
```

Out[74]:

	domestic_gross	foreign_gross	year	total_gross	start_year	runtime_minutes	averagerating	numvotes	worldwide_gross
count	1.936000e+03	1.321000e+03	1947.000000	1.310000e+03	1947.000000	1937.000000	1921.000000	1.921000e+03	1.310000e+03
mean	4.215604e+07	9.408001e+07	2014.022085	1.544118e+08	2014.022085	110.261745	6.422124	9.064797e+04	1.544118e+08
std	7.622377e+07	1.509268e+08	2.511438	2.242633e+08	2.511438	20.422352	1.001860	1.484956e+05	2.242633e+08
min	3.000000e+02	6.000000e+02	2010.000000	4.940000e+04	2010.000000	5.000000	1.600000	6.000000e+00	4.940000e+04
25%	5.587500e+05	7.400000e+06	2012.000000	2.174525e+07	2012.000000	96.000000	5.800000	7.359000e+03	2.174525e+07
50%	1.070000e+07	3.100000e+07	2014.000000	6.860000e+07	2014.000000	107.000000	6.500000	3.481600e+04	6.860000e+07
75%	5.097500e+07	1.033000e+08	2016.000000	1.776000e+08	2016.000000	122.000000	7.100000	1.051160e+05	1.776000e+08
max	7.001000e+08	9.464000e+08	2018.000000	1.405400e+09	2018.000000	189.000000	8.900000	1.841066e+06	1.405400e+09

Importing another SQL library to run queries on the new merged dataframe.

In [75]:

```
!pip install pandasql
```

```
Requirement already satisfied: pandasql in c:\users\fortu\anaconda3\envs\learn-env\lib\site-packages (0.7.3)
Requirement already satisfied: pandas in c:\users\fortu\anaconda3\envs\learn-env\lib\site-packages (from pandasql) (1.
1.3)
Requirement already satisfied: sqlalchemy in c:\users\fortu\anaconda3\envs\learn-env\lib\site-packages (from pandasql)
(1.3.19)
Requirement already satisfied: numpy in c:\users\fortu\anaconda3\envs\learn-env\lib\site-packages (from pandasql) (1.1
8.5)
Requirement already satisfied: python-dateutil>=2.7.3 in c:\users\fortu\anaconda3\envs\learn-env\lib\site-packages (fr
om pandas->pandasql) (2.8.1)
Requirement already satisfied: pytz>=2017.2 in c:\users\fortu\anaconda3\envs\learn-env\lib\site-packages (from pandas-
>pandasql) (2020.1)
Requirement already satisfied: six>=1.5 in c:\users\fortu\anaconda3\envs\learn-env\lib\site-packages (from python-date
util>=2.7.3->pandas->pandasql) (1.15.0)
```

In [76]:

```
import pandasql as psql
```

Now I am going to determine the genres of the highest grossing films.

In [77]:

```
query = """
SELECT genres, title, year, MAX(worldwide_gross) AS max_gross
FROM merged_df
WHERE genres IS NOT NULL AND worldwide_gross IS NOT NULL
GROUP BY genres
ORDER BY max_gross DESC
"""
gross_by_genres = psql.sqldf(query, locals())
gross_by_genres
```

Out[77]:

	genres	title	year	max_gross
0	Action,Adventure,Sci-Fi	Avengers: Age of Ultron	2015	1.405400e+09
1	Action,Adventure,Fantasy	Star Wars: The Last Jedi	2017	1.332600e+09
2	Adventure,Animation,Comedy	Frozen	2013	1.276400e+09
3	Action,Adventure,Animation	Incredibles 2	2018	1.242800e+09
4	Action,Adventure,Thriller	Skyfall	2012	1.108600e+09
...	...	...	...	...
208	Biography,Comedy,Crime	Casino Jack	2010	1.040700e+06
209	Crime,Drama,Romance	Ain't Them Bodies Saints	2013	1.032000e+06
210	Action,Horror,Mystery	Universal Soldier: Day of Reckoning	2012	3.695000e+05
211	Thriller,Western	Red Hill	2010	3.211000e+05
212	Documentary,History	Eyes Wide Open	2010	2.763000e+05

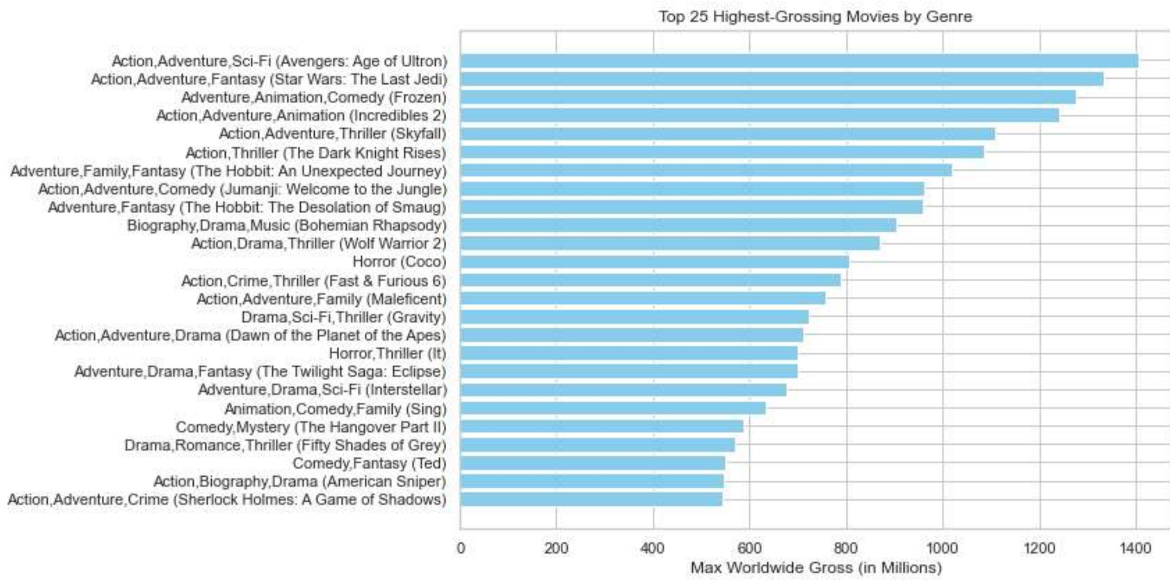
213 rows × 4 columns

In [78]:
```
gross_by_genres['max_gross_million'] = gross_by_genres['max_gross'] / 1_000_000
gross_by_genres['max_gross_million'] = gross_by_genres['max_gross_million'].round(1).astype(str) + 'M'
gross_by_genres[['genres', 'title', 'year', 'max_gross_million']].head(25)
```

Out[78]:

	genres	title	year	max_gross_million
0	Action,Adventure,Sci-Fi	Avengers: Age of Ultron	2015	1405.4M
1	Action,Adventure,Fantasy	Star Wars: The Last Jedi	2017	1332.6M
2	Adventure,Animation,Comedy	Frozen	2013	1276.4M
3	Action,Adventure,Animation	Incredibles 2	2018	1242.8M
4	Action,Adventure,Thriller	Skyfall	2012	1108.6M
5	Action,Thriller	The Dark Knight Rises	2012	1084.9M
6	Adventure,Family,Fantasy	The Hobbit: An Unexpected Journey	2012	1021.1M
7	Action,Adventure,Comedy	Jumanji: Welcome to the Jungle	2017	962.1M
8	Adventure,Fantasy	The Hobbit: The Desolation of Smaug	2013	958.4M
9	Biography,Drama,Music	Bohemian Rhapsody	2018	903.6M
10	Action,Drama,Thriller	Wolf Warrior 2	2017	870.3M
11	Horror	Coco	2017	807.1M
12	Action,Crime,Thriller	Fast & Furious 6	2013	788.7M
13	Action,Adventure,Family	Maleficent	2014	758.5M
14	Drama,Sci-Fi,Thriller	Gravity	2013	723.2M
15	Action,Adventure,Drama	Dawn of the Planet of the Apes	2014	710.6M
16	Horror,Thriller	It	2017	700.4M
17	Adventure,Drama,Fantasy	The Twilight Saga: Eclipse	2010	698.5M
18	Adventure,Drama,Sci-Fi	Interstellar	2014	677.4M
19	Animation,Comedy,Family	Sing	2016	634.2M
20	Comedy,Mystery	The Hangover Part II	2011	586.8M
21	Drama,Romance,Thriller	Fifty Shades of Grey	2015	571.0M
22	Comedy,Fantasy	Ted	2012	549.4M
23	Action,Biography,Drama	American Sniper	2014	547.4M
24	Action,Adventure,Crime	Sherlock Holmes: A Game of Shadows	2011	545.4M

In [79]:
```
top25 = gross_by_genres.head(25)
top25 = top25.copy()
top25['max_gross'] = top25['max_gross'] / 1_000_000
top25['label'] = top25['genres'] + ' (' + top25['title'] + ')'
plt.figure(figsize=(12, 6))
plt.barh(top25['label'], top25['max_gross'], color='skyblue')
plt.xlabel('Max Worldwide Gross (in Millions)')
plt.title('Top 25 Highest-Grossing Movies by Genre')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```



As displayed in the above graphic, action and adventure films have dominated the list of highest grossing films.

In [80]:
```
total_gross = gross_by_genres['max_gross'].sum()
print(f"Total gross (Top 25): ${total_gross:,.2f}M")
```

```
Total gross (Top 25): $50,631,246,299.00M
```

In [92]:
```
gross_by_genres['percentage'] = (gross_by_genres['max_gross'] / total_gross) * 100
gross_by_genres[['title','genres', 'max_gross', 'percentage']].head()
```

Out[92]:

	title	genres	max_gross	percentage
0	Avengers: Age of Ultron	Action,Adventure,Sci-Fi	1.405400e+09	2.775756
1	Star Wars: The Last Jedi	Action,Adventure,Fantasy	1.332600e+09	2.631972
2	Frozen	Adventure,Animation,Comedy	1.276400e+09	2.520973
3	Incredibles 2	Action,Adventure,Animation	1.242800e+09	2.454611
4	Skyfall	Action,Adventure,Thriller	1.108600e+09	2.189557

In [94]:
```
top_genre = gross_by_genres.loc[gross_by_genres['max_gross'].idxmax()]
print(f"Top genre: {top_genre['genres']} grossed ${top_genre['max_gross']:,.0f}M, "
      f"which is {top_genre['percentage']:.2f}% of the top 25 total.")
```

```
Top genre: Action,Adventure,Sci-Fi grossed $1,405,400,000M, which is 2.78% of the top 25 total.
```

In [97]:

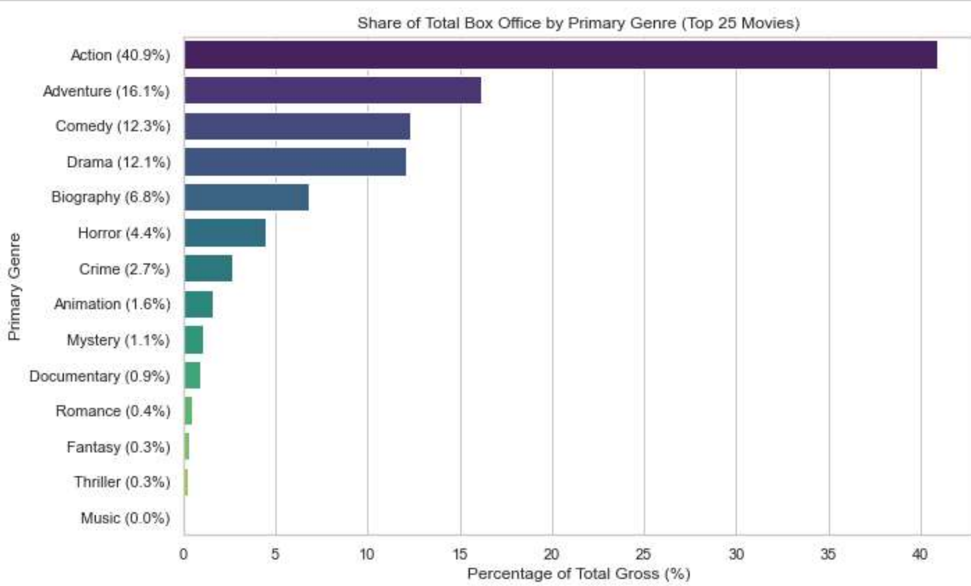
```
gross_by_genres['primary_genre'] = gross_by_genres['genres'].apply(lambda x: x.split(',')[0])

genre_summary = gross_by_genres.groupby('primary_genre')['max_gross'].agg(['count', 'sum']).reset_index()
total_gross = genre_summary['sum'].sum()
genre_summary['percentage'] = (genre_summary['sum'] / total_gross) * 100

genre_summary['label'] = genre_summary['primary_genre'] + ' (' + genre_summary['percentage'].round(1).astype(str) + '%)

genre_summary = genre_summary.sort_values('sum', ascending=False)
genre_summary
```

Out[97]:

	primary_genre	count	sum	percentage	label
0	Action	55	2.071997e+10	40.923291	Action (40.9%)
1	Adventure	28	8.175633e+09	16.147406	Adventure (16.1%)
4	Comedy	38	6.222054e+09	12.288961	Comedy (12.3%)
7	Drama	34	6.133205e+09	12.113478	Drama (12.1%)
3	Biography	15	3.438841e+09	6.791934	Biography (6.8%)
9	Horror	6	2.249600e+09	4.443106	Horror (4.4%)
5	Crime	11	1.344332e+09	2.655143	Crime (2.7%)
2	Animation	7	8.074050e+08	1.594677	Animation (1.6%)
11	Mystery	2	5.549000e+08	1.095964	Mystery (1.1%)
6	Documentary	7	4.527846e+08	0.894279	Documentary (0.9%)
12	Romance	3	2.242540e+08	0.442916	Romance (0.4%)
8	Fantasy	4	1.664444e+08	0.328739	Fantasy (0.3%)
13	Thriller	2	1.338211e+08	0.264305	Thriller (0.3%)
10	Music	1	8.000000e+06	0.015801	Music (0.0%)

In [99]:

```
plt.figure(figsize=(10, 6))
sns.barplot(data=genre_summary, x='percentage', y='label', palette='viridis')
plt.title("Share of Total Box Office by Primary Genre (Top 25 Movies)")
plt.xlabel("Percentage of Total Gross (%)")
plt.ylabel("Primary Genre")
plt.tight_layout()
plt.show()
```



Breaking that down further, the gross revenue of the top 25 movies is comprised 40.9% by action films, followed by 16.1% by adventure films.

Now that we know which genres to focus on, we'll look for potential directors for our film studio.

In [85]:

```
pd.read_sql("""
SELECT primary_name AS director_name, AVG(averagerating) AS avg_director_rating, COUNT(*) AS movie_count
FROM directors
JOIN persons ON directors.person_id = persons.person_id
JOIN movie_ratings ON directors.movie_id = movie_ratings.movie_id
GROUP BY primary_name
HAVING COUNT(*) >= 10
ORDER BY avg_director_rating DESC
LIMIT 50;
""", conn)
```

Out[85]:

	director_name	avg_director_rating	movie_count
0	Nuo Wang	9.100000	10
1	Corey Lubowich	9.100000	12
2	Sylvia Broeckx	9.000000	28
3	Lisa Gossels	9.000000	17
4	Erin Korbylo	9.000000	28
5	Dennis Korbylo	9.000000	28
6	Elizabeth Blake-Thomas	8.671429	14
7	Steve Ravic	8.654545	11
8	Tom Logan	8.610000	10
9	Yazan Khalili	8.600000	10
10	Muhannad Salahat	8.600000	10
11	Ayman Azraq	8.600000	10
12	Asma Ghannem	8.600000	10
13	Asem Nasser	8.600000	10
14	Ameen Nayfeh	8.600000	10
15	Alaa Al-Ali	8.600000	10
16	Jason Reid	8.566667	12
17	Mahdi Fleifel	8.527273	11
18	Rishab Shetty	8.500000	10
19	Christian Palmer	8.480000	10
20	Damir Cucic	8.418182	11
21	William Gabriel Grier	8.400000	11
22	Scott Trost	8.400000	11
23	P.J. Ochlan	8.400000	11
24	Nicholas Acosta	8.400000	11
25	Matthew M Stevens	8.400000	11
26	Marie-Lise Tombeur	8.400000	10
27	Logan Leistikow	8.400000	10
28	Lincoln Hoppe	8.400000	11
29	Laura Azevedo	8.400000	11
30	Lacy McClory	8.400000	11
31	Kim Beavers	8.400000	11
32	Kathleen Randazzo	8.400000	11
33	Joachim Huveneers	8.400000	10
34	Joachim Dejonghe	8.400000	10
35	Jim Süter	8.400000	10
36	Dries Deboiserie	8.400000	10
37	Doug van Bebber	8.400000	11
38	Charles Bockaert	8.400000	10
39	Aram Shahbazyan	8.383333	12
40	Paulo César Fajardo	8.323077	13
41	Nick Lang	8.300000	10
42	Scott Rhodes	8.272727	11
43	Tarzan Nasser	8.250000	12
44	Arab Nasser	8.250000	12
45	Anthony Russo	8.246667	30
46	Nick Rosen	8.236364	11
47	Peter Mortimer	8.221429	14
48	Josh Lowell	8.221429	14
49	Miles Watts	8.208333	12

Now we're going to adjust our parameters slight, so that we can find directors who produce action and/or adventure films with consistent high ratings. We also want to ensure they have experience with several productions, so they must have directed at least 10 action and/or adventure films.

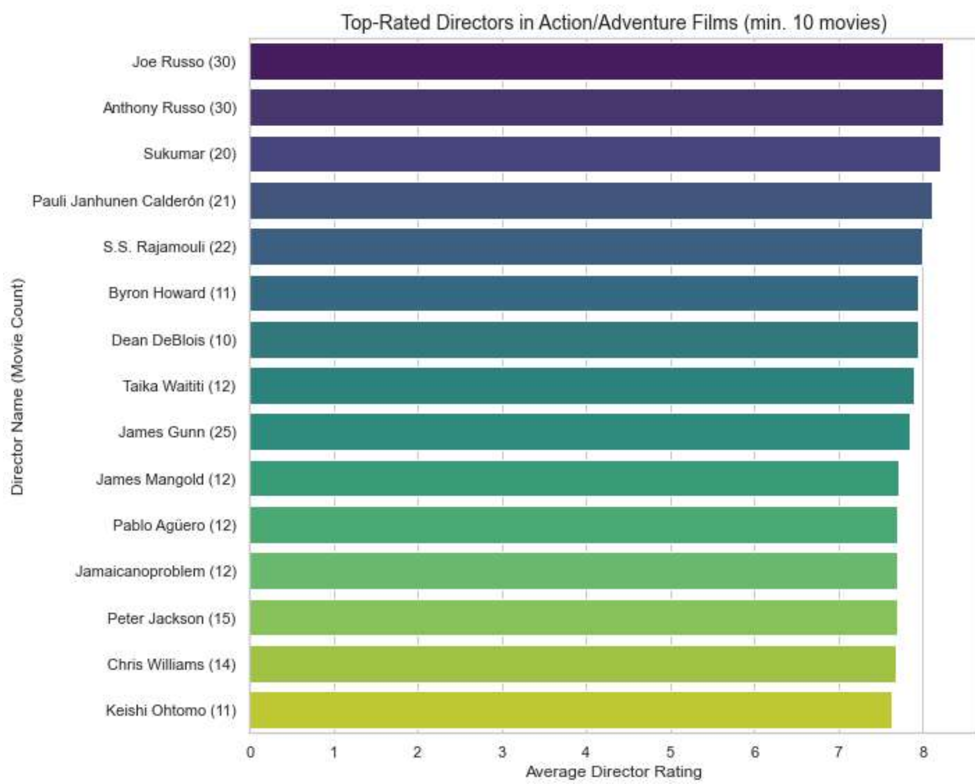
In [86]:

```
director_movie_ratings = pd.read_sql("""
SELECT
    primary_name AS director_name,
    AVG(averagerating) AS avg_director_rating,
    COUNT(*) AS movie_count
FROM directors
JOIN persons ON directors.person_id = persons.person_id
JOIN movie_ratings ON directors.movie_id = movie_ratings.movie_id
JOIN movie_basics ON directors.movie_id = movie_basics.movie_id
WHERE genres LIKE '%Action%' OR genres LIKE '%Adventure%'
GROUP BY primary_name
HAVING COUNT(*) >= 10
ORDER BY avg_director_rating DESC
LIMIT 50;
""", conn)
director_movie_ratings
```

Out[86]:

	director_name	avg_director_rating	movie_count
0	Joe Russo	8.246667	30
1	Anthony Russo	8.246667	30
2	Sukumar	8.210000	20
3	Pauli Janhunen Calderón	8.109524	21
4	S.S. Rajamouli	7.986364	22
5	Byron Howard	7.945455	11
6	Dean DeBlois	7.940000	10
7	Taika Waititi	7.900000	12
8	James Gunn	7.840000	25
9	James Mangold	7.716667	12
10	Pablo Agüero	7.700000	12
11	Jamaicanoproblem	7.700000	12
12	Peter Jackson	7.700000	15
13	Chris Williams	7.685714	14
14	Keishi Ohtomo	7.636364	11
15	Keitarô Motonaga	7.621429	14
16	Rich Moore	7.595652	23
17	Matthew Vaughn	7.500000	20
18	J.G. Quintel	7.500000	11
19	Anurag Kashyap	7.486667	15
20	Don Hall	7.483333	24
21	Phil Lord	7.421053	19
22	Christopher Miller	7.421053	19
23	Chris McKay	7.300000	14
24	Nikolay Yeriomin	7.228571	14
25	Guy Ritchie	7.214286	14
26	Stephen J. Anderson	7.200000	10
27	Peyton Reed	7.193333	15
28	Trivikram Srinivas	7.156250	16
29	Bryan Singer	7.146667	15
30	Marc Forster	7.146154	13
31	Justin Lin	7.140000	10
32	Kazuchika Kise	7.113333	15
33	Sergey A.	7.110526	38
34	Radha Krishna Jagarlamudi	7.092857	14
35	Joseph Kosinski	7.075000	12
36	Hiromasa Yonebayashi	7.072727	11
37	S. Shankar	7.033333	12
38	Shôjirô Nakazawa	7.030000	10
39	Jeff Tremaine	7.000000	25
40	Peter Berg	6.988235	17
41	Gareth Edwards	6.983333	12
42	Mohan Raja	6.975000	12
43	Surrender Reddy	6.969231	13
44	Bejoy Nambiar	6.960870	23
45	Masaaki Yuasa	6.960000	10
46	Ron Howard	6.910000	10
47	Vardan Tozija	6.900000	10
48	Srdjan Janicijevic	6.900000	10
49	Sinisa Evtimov	6.900000	10

In [87]:
```
top_directors = director_movie_ratings.sort_values(by='avg_director_rating', ascending=False).head(15).copy()
top_directors['label'] = top_directors['director_name'] + ' (' + top_directors['movie_count'].astype(str) + ')'
sns.set(style="whitegrid")
plt.figure(figsize=(10, 8))
barplot = sns.barplot(
    x='avg_director_rating',
    y='label',
    data=top_directors,
    palette='viridis'
)
plt.title('Top-Rated Directors in Action/Adventure Films (min. 10 movies)', fontsize=14)
plt.xlabel('Average Director Rating')
plt.ylabel('Director Name (Movie Count)')
plt.tight_layout()
plt.show()
```



Now we have our list of potential directors to contact.

Now we'll do a similar search, this time for actors. Will filter for actors and actresses who have starred in at least 10 action and/or adventure films and have receieved consistently high reviews.

In [88]:
```
pd.read_sql("""
SELECT * FROM principals
;""", conn)
```

Out[88]:

	movie_id	ordering	person_id	category	job	characters
0	tt0111414	1	nm0246005	actor	None	["The Man"]
1	tt0111414	2	nm0398271	director	None	None
2	tt0111414	3	nm3739909	producer	producer	None
3	tt0323808	10	nm0059247	editor	None	None
4	tt0323808	1	nm3579312	actress	None	["Beth Boothby"]
...	...	...	...	...	...	...
1028181	tt9692684	1	nm0186469	actor	None	["Ebenezer Scrooge"]
1028182	tt9692684	2	nm4929530	self	None	["Herself","Regan"]
1028183	tt9692684	3	nm10441594	director	None	None
1028184	tt9692684	4	nm6009913	writer	writer	None
1028185	tt9692684	5	nm10441595	producer	producer	None

1028186 rows × 6 columns

In [100]:

```
actor_movie_ratings = pd.read_sql("""
SELECT
    p.primary_name AS actor_name,
    AVG(mr.averagerating) AS avg_movie_rating,
    COUNT(*) AS movie_count
FROM principals pr
JOIN persons p ON pr.person_id = p.person_id
JOIN movie_basics mb ON pr.movie_id = mb.movie_id
JOIN movie_ratings mr ON pr.movie_id = mr.movie_id
JOIN movie_akas ma ON pr.movie_id = ma.movie_id
WHERE
    (mb.genres LIKE '%Action%' OR mb.genres LIKE '%Adventure%')
    AND pr.category IN ('actor', 'actress')
    AND mr.averagerating >= 7.0
    AND (ma.region = 'US' OR ma.language = 'en')
GROUP BY p.primary_name
HAVING COUNT(*) >= 10
ORDER BY avg_movie_rating DESC
LIMIT 50;
""", conn)
actor_movie_ratings
```

Out[100]:

	actor_name	avg_movie_rating	movie_count
0	Anne Hathaway	8.476923	13
1	Gary Oldman	8.240000	10
2	Mark Ruffalo	8.212500	24
3	Tom Hardy	8.207143	14
4	Chris Evans	8.027500	40
5	Chris Hemsworth	8.006667	30
6	Morena Baccarin	7.885714	14
7	Scarlett Johansson	7.868421	19
8	Kevin T. Collins	7.833333	12
9	Carrie Keranen	7.833333	12
10	Samantha Ruth Prabhu	7.823077	13
11	Robert Downey Jr.	7.807843	51
12	Ryan Reynolds	7.800000	16
13	Domhnall Gleeson	7.781818	11
14	Iko Uwais	7.763636	11
15	Hiroaki Iwanaga	7.760000	10
16	Emily Blunt	7.757143	14
17	Ian McKellen	7.747059	17
18	Amy Poehler	7.728571	14
19	Hugh Jackman	7.709091	11
20	Takahiro Sakurai	7.675000	32
21	Richard Armitage	7.669231	13
22	Chloë Grace Moretz	7.654545	11
23	Christopher Sabat	7.650000	12
24	Cate Blanchett	7.646667	15
25	James McAvoy	7.646154	13
26	John Boyega	7.625000	12
27	Daisy Ridley	7.625000	12
28	Martin Freeman	7.621429	14
29	Zoe Saldana	7.620000	20
30	J. Michael Tatum	7.618750	16
31	Jeremy Renner	7.610000	20
32	Andy Serkis	7.606667	15
33	Eric Vale	7.605556	18
34	Bridgit Mendler	7.600000	11
35	Chris Pratt	7.593750	16
36	Will Arnett	7.568750	16
37	Jun Fukuyama	7.552941	17
38	Yukana Nogami	7.543750	16
39	Josh Brolin	7.542308	26
40	Samuel L. Jackson	7.521429	14
41	Jon Bernthal	7.518182	11
42	Moises Arias	7.514286	14
43	Andrey Merzlikin	7.500000	11
44	Aleksey Kopashov	7.500000	11
45	Aleksandr Korshunov	7.500000	11
46	Jennifer Lawrence	7.487500	16
47	Tom Cruise	7.470270	37
48	Pavel Derevyanko	7.453846	13
49	Donnie Yen	7.452941	17

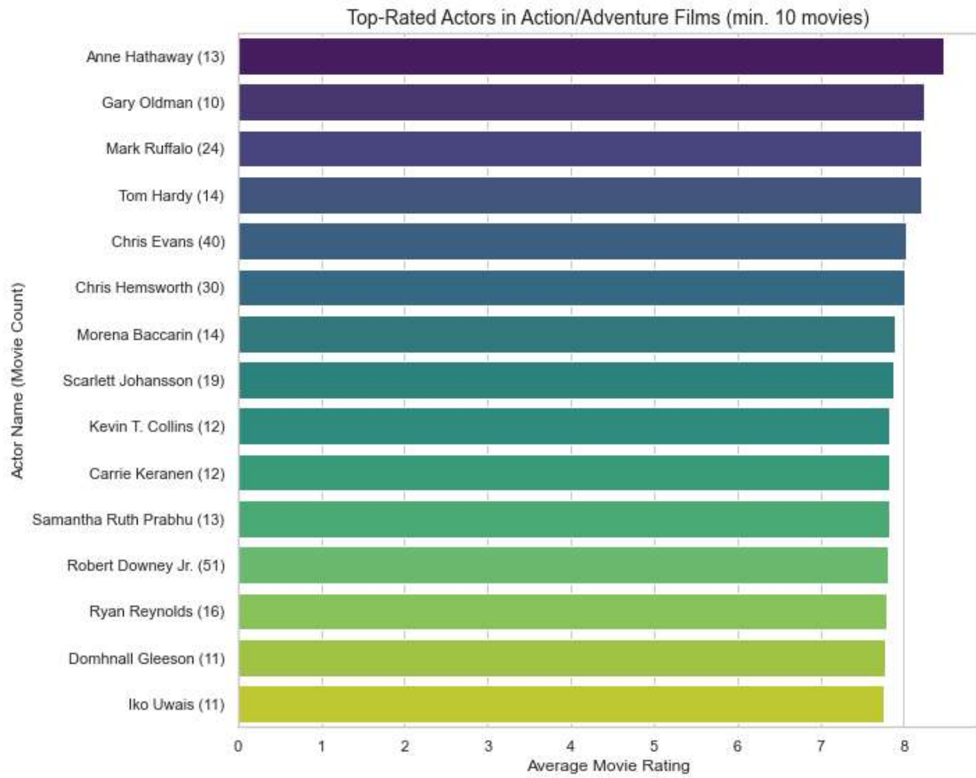
In [101]:

```
print(actor_movie_ratings.columns)
```

```
Index(['actor_name', 'avg_movie_rating', 'movie_count'], dtype='object')
```

In [102]:

```
top_actors = actor_movie_ratings.sort_values(by='avg_movie_rating', ascending=False).head(15).copy()
top_actors['label'] = top_actors['actor_name'] + ' (' + top_actors['movie_count'].astype(str) + ')'
sns.set(style="whitegrid")
plt.figure(figsize=(10, 8))
barplot = sns.barplot(
    x='avg_movie_rating',
    y='label',
    data=top_actors,
    palette='viridis'
)
plt.title('Top-Rated Actors in Action/Adventure Films (min. 10 movies)', fontsize=14)
plt.xlabel('Average Movie Rating')
plt.ylabel('Actor Name (Movie Count)')
plt.tight_layout()
plt.show()
```



And now we have our list of potential stars to contact.

Conclusions

Action and adventure films have performed well at the box office. The high grossing performance of these films indicates a large audience of viewers who enjoy these genres. The company can do well in this industry by working with the right individuals to direct and star in our films.

Limitations

This initial analysis did not include average production and hiring costs per genre or movie. Potential budget constraints of our new movie studio may affect which route management decides to pursue, whether it be in the action/adventure genre or otherwise.

Recommendations

I recommend the company review the list of potential directors and actors, and then develop an initial budget for the studio. Once we determine how much we are willing to spend on production and on procuring talent, we can examine the costs of hiring directors and actors suggested from the analysis and generate a more accurate candidate list.

Next Steps

Following this initial analysis, we can search for potential writers and producers using these same data sources.